# Maximizing Sensor Lifetime in A Rechargeable Sensor Network via Partial Energy Charging on Sensors

Wenzheng Xu†, Weifa Liang‡, Xiaohua Jia¶, and Zichuan Xu‡
† College of Computer Science, Sichuan University, Chengdu 610065, P. R. China
‡ Research School of Computer Science, The Australian National University, Canberra, ACT 2601, Australia
¶ Department of Computer Science, City University of Hong Kong, P. R. China
Emails: wenzheng.xu3@gmail.com, wliang@cs.anu.edu.au, csjia@cityu.edu.hk, edward.xu@anu.edu.au

***Abstract*—The wireless energy transfer technology based on magnetic resonant coupling has emerged as a promising technology for wireless sensor networks, by providing controllable yet perpetual energy to sensors. In this paper we study the use of a mobile charger to wirelessly charge sensors in a rechargeable sensor network so that the sum of sensor lifetimes is maximized while the traveling distance of the mobile charger is minimized. Unlike existing studies that assumed a mobile charger must charge a sensor to its full energy capacity before moving to charge the next sensor, in this paper we assume that each sensor can be partially charged so that more sensors can be charged by the mobile charger before their energy depletions. Under this new charging model, we first formulate a novel optimization problem of scheduling the mobile charger to charge life-critical sensors with an objective to maximize the sum of sensor lifetimes, while minimizing the traveling distance of the mobile charger. Due to NP-hardness of the problem, we then propose an efficient algorithm for it. We finally evaluate the performance of the proposed algorithm through experimental simulations. Simulation results demonstrate that the proposed algorithm is very promising.**

## I. Introduction

The wireless energy transfer based on magnetic resonant coupling revolutionizes energy supplies to wireless sensor networks (WSNs) [4], [6], [16]. Unlike sensor replenishments through energy harvesting that only provide temporally and spatially varying energy sources (e.g., solar energy and wind energy) [9], [10], the deployment of mobile chargers (i.e., mobile charging vehicles) to charge sensors wirelessly has been a new promising technology that ensures sensors can be charged with high yet reliable charging rates, thereby they can operate perpetually [6], [7], [11], [14], [15], [16], [17], [18]. It is however very challenging to design efficient charging scheduling algorithms for mobile chargers, due to the inherent constraints on WSNs such as (i) the energy consumption rates of different sensors are significantly different. Sensors near to the base station have to relay data for the other remote sensors and thus consume much more energy than others [15]. In addition, the energy consumption rate of each sensor may change over time as its sensing data rate usually depends on the specific application of the WSN [12], [13]. (ii) The battery technology has not been much improved in the past decades. It still takes a long time (e.g., 30-80 minutes) to fully charge a commercial off-the-shelf sensor battery [12]. (iii) The mobile charger consumes its energy not only on sensor charging but also on its mechanical movement, thereby incurring high charging costs [13], [16].

Several pioneering works have been conducted recently to address the mentioned challenges [14], [8], [11], [13]. For example, Xu *et al.* [14] studied the problem of scheduling $k$ mobile chargers to charge a set of sensors so that all the sensors in the set can be fully charged as quickly as possible, while Ren *et al.* [8] investigated the problem of dispatching a mobile charger to charge as many sensors as possible within a given time period. Shi *et al.* [11] employed a mobile charger to charge all sensors periodically such that the network can operate perpetually. Given a set of to-be-charged sensors with different residual lifetimes, Wang *et al.* [13] devised an adaptive algorithm to schedule a mobile charger to charge a proportion of sensors with an objective to maximize the amount of energy charged to sensors minus the amount of energy consumed on the mobile charger's traveling, while ensuring that each chosen sensor will be charged prior to its energy expiration.

Although the above mentioned studies strive for the finest trade-off between charging as many sensors as possible in time and minimizing the traveling distance of the mobile charger, there are two major limits in these studies. First, they all assumed that a mobile charger must charge a sensor to its full energy capacity if the sensor will be charged. Since fully charging a commercial off-the-shelf sensor battery (e.g., Lithium battery) takes a while (e.g., 30-80 minutes) [12], this full-charging model will prevent the mobile charger from charging more sensors before these sensors expire their energy completely, especially when there are multiple life-critical sensors to be charged at that moment. We here use an example to illustrate such a scenario. Assume that a WSN consists of two sensors $u$ and $v$ only, the residual lifetime of each the two sensors is 10 minutes, and it takes an hour to fully charge either of them. If we deploy one mobile charger to charge them by adopting the full-charging model, then one of them will be charged before its energy depletion, while the other must be dead for a period of 60-10=50 minutes before it can be charged, assuming that the traveling time of the mobile charger between the two sensors is ignored. In contrast, if a partial-charging model is adopted, the mobile charger can first charge sensor $u$ for 10 minutes (the amount of energy charged to sensor $u$ can support its operations for a while, e.g., 5 fours), then charge sensor $v$ to its full energy capacity, and finally charge sensor $u$ to its full energy capacity. It can be seen that under the partial-charging model, both of the two sensors can be charged prior to their energy expirations. Note that although adopting the partial-charging model may increase the traveling distance of the mobile charger, such an increase on the travel distance is worthy since the continuing operation of sensors is a fundamental requirement for most WSN applications. Otherwise, no sensing data will be generated by the dead sensors or "fresh" sensing data generated by other live sensors cannot be forwarded to the base station due to their dead relay sensors. The second limit is that most existing studies only considered charging as many sensors as possible before they run out of energy but ignore shortening the energy expiration durations of sensors. Thus, some sensors can continue their operations without energy depletions while the others may have been dead for a long time before they can be charged again. Notice that the energy expirations of sensors for a long time may

978-1-5090-1732-4/16/$31.00 ©2016 IEEE

lead to severe consequences. For example, in a WSN for early forest fire detections [3], the energy depletions of some sensors for several hours may delay the detection of a forest fire. Such a detection delay may result in the fire uncontrollable, eventually incurring significant damages and casualties, since the forest fire can be quickly spread by strong wind in a very short time [3].

Unlike existing studies that adopt the full-charging model, in this paper we adopt a novel partial-charging model so that more sensors can be charged before their energy depletions or their energy expiration durations can be significantly shortened. Under this new partial-charging model, we investigate the problem of finding a charging tour for a mobile charger to charge a set of life-critical sensors so that the sum of sensor lifetimes is maximized, while keeping the traveling distance of the charger minimized. The challenges of this problem are as follows. (i) What is the amount of energy to be charged to each sensor each time? (ii) Which schedule can maximize the sum of sensor lifetimes? and (iii) How to find a charging tour for the mobile charger so that its traveling distance is minimized? We note that these challenges have not been addressed by existing studies, and most of existing work assumed that each sensor can only be charged once per charging tour while we here allow that each sensor can be charged multiple times and the amount of energy charged to it each time can be different. Also, existing work only focused on charging as many sensors as possible in time while we aim to maximize the sum of sensor lifetimes. In this paper we tackle the challenges by first formulating a novel optimization problem, and then devising an efficient algorithm for the problem.

The main contributions of this paper can be summarized as follows. We are the first to propose a partial-charging model to increase sensor survival opportunities. We then formulate a novel optimization problem of scheduling a mobile charger to charge a set of sensors wirelessly, and propose an efficient scheduling algorithm for the problem. We finally evaluate the performance of the proposed algorithm through experimental simulations. The simulation results demonstrate that the proposed algorithm is very promising. Especially, the average energy expiration duration per sensor by the proposed algorithm is only 10% of that by the state-of-the-art algorithm while the traveling distance of the mobile charger by the algorithm is only about from 7% to 18% longer than that by the state-of-the-art.

The remainder of the paper is organized as follows. Section II introduces the system model, notations, notions, and problem definitions. Section III calculates the maximum sum of sensor lifetimes, and Section IV proposes an efficient charging scheduling algorithm so that the traveling distance of the mobile charger minimized while keeping the sum of sensor lifetimes is maximized. Section V evaluates the performance of the proposed algorithm. Section VI reviews related studies, and Section VII concludes the paper.

## II. Preliminaries

### A. Network model

We consider a rechargeable wireless sensor network $G_s = (V_s, E_s)$ deployed for environmental monitoring or event detections, where $V_s$ is a set of sensors and a base station. There is an edge in $E_s$ between any two sensors or a sensor and the base station if they are within the communication range of each other. Each sensor $v_i \in V_s$ is powered by a rechargeable battery with energy capacity $B_i$. Let $b_i(t)$ be the sensing data rate of sensor $v_i$ at time $t$, which may vary over time. We assume that there is a routing protocol in $G_s$ for sensing data collection that relays sensing data from individual sensors to the base station through multihop relays. For example, each sensor can upload its sensing data to the base station via a routing path with the minimum energy consumption.

Notice that each sensor will consume its battery energy when performing sensing, data transmission and reception [5]. We assume that each sensor $v_i \in V_s$ can monitor its residual energy $RE_i(t)$ and estimate its energy consumption rate $\hat{\rho}_i(t)$ in the near future, by adopting existing prediction techniques such as linear regressions. For example, $\hat{\rho}_i(t) = \omega\rho_i(t-1) + (1-\omega)\hat{\rho}_i(t-1)$, where $\hat{\rho}_i$ is the estimation and $\rho_i$ is the actual value at that moment and $\omega$ is a weight between 0 and 1. The base station keeps a copy of the energy depletion rate $\rho_i(t)$ and the residual energy $RE_i(t)$ of each sensor $v_i \in V_s$. Let $\theta > 0$ be a given threshold, the updating of each sensor $v_i \in V_s$ on its energy consumption rate is performed as follows. If $|\hat{\rho}_i(t) - \hat{\rho}_i(t-1)| \leq \theta$, no updating report is needed; otherwise, the updated energy consumption rate and the residual energy of $v_i$ will be reported to the base station, and the base station performs necessary updating accordingly. *The residual lifetime* $l_i(t)$ of each sensor $v_i$ at time $t$ is $l_i(t) = \frac{RE_i(t)}{\hat{\rho}_i(t)}$.

### B. Charging model

To maintain the long-term operation of a sensor network $G_s$, its sensors will be charged by a mobile charger (i.e., a charging vehicle) located at a depot $r$ at some certain time points. For simplicity, in this paper we assume that there is only one mobile charger that is located at a depot within the monitoring area of the WSN. The proposed algorithms can be easily extended to a network with multiple mobile chargers. The mobile charger starts from its depot to perform its charging tour and returns to the depot for recharging itself after the tour, and it can charge its nearby sensor (e.g., within 2 meters) with a fixed charging rate $\mu$ and move at a speed $\nu$.

Since the energy consumption rate of each sensor may experience significant changes in a monitoring period. A sensor $v_i \in V_s$ sends a charging request $REQ_i = (t, v_i, RE_i, \rho_i, B_i - RE_i)$ to the base station when its residual lifetime $l_i$ is below a given critical lifetime $l_c$ (e.g., 2 hours) at time point $t$, where the charging request $REQ_i$ contains the time point $t$ issuing the request, the sensor ID $v_i$, its residual energy $RE_i$, its energy consumption rate $\rho_i$, and the maximum amount of energy $B_i - RE_i$ that can be charged. Once receiving the charging request from sensor $v_i$, the base station then dispatches the mobile charger to charge sensor $v_i$ as well as some other life-critical sensors in the network. Let $V_1$ be the set of sensors with residual lifetimes below the critical lifetime $l_c$, i.e., $V_1 = \{v_i \mid v_i \in V_s, l_i \leq l_c\}$, and $V_2 = V_s \setminus V_1$. We assume that the duration spent on its traveling by the mobile charger per charging tour is much shorter than its time spent on charging sensors [15]. We further assume that the energy consumption rate of a sensor does not fluctuate too much within a charging tour, or such minor fluctuations can be neglected as the duration of a charging tour usually is short. But the energy consumption rate of each sensor is allowed to change at different charging tours. To ensure that the base station will not receive any charging requests from other sensors before the mobile charger finishes its current charging task, we find a set $V (\subseteq V_s)$ of to-be-charged sensors so that the total time for charging the sensors in $V$ is less than the residual lifetime of each sensor in $V_s \setminus V$ minus the critical lifetime $l_c$, i.e., $\sum_{v_i \in V} \frac{B_i - RE_i}{\mu} < l_j - l_c$ for each sensor $v_j \in V_s \setminus V$, where $\mu$ is the charging rate of the mobile charger. Initially, let $V = V_1$ and $v_1, v_2, \ldots, v_{n_2}$ be the sensors in $V_2 = V_s \setminus V_1$ with $n_2 = |V_2|$. For simplicity, assume that $l_1 \le l_2 \le \cdots \le l_{n_2}$, where $l_j$ is the residual lifetime of sensor $v_j \in V_2$. If $\sum_{v_i \in V_1} \frac{B_i - RE_i}{\mu} < l_1 - l_c$, then $V = V_1$ is the current set of to-be-charged sensors. Otherwise, we move sensor $v_1$ from set $V_2$ to $V$. This procedure continues until a sensor $v_j$ with $\sum_{v_i \in V_1} \frac{B_i - RE_i}{\mu} + \sum_{j'=1}^{j-1} \frac{B_{j'} - RE_{j'}}{\mu} < l_j - l_c$ has been identified, and the set of to-be-charged sensors then is $V = V_1 \cup \{v_1, v_2, \ldots, v_{j-1}\}$.

A novel *partial-charging* model is proposed as follows. Recall that $RE_i$ is the amount of residual energy of sensor $v_i$ at some time point $t$. The amount of energy that can be charged to sensor $v_i$ at each time then ranges from 0 to $B_i - RE_i$, where $B_i$ is the battery capacity of sensor $v_i$. Although we allow each sensor to be partially charged, it is not economical to charge only a small amount of energy to the sensor at each time, since the traveling distance of the mobile charger can be significantly increased by scheduling the charger to visit the sensor many times in a single charging tour. We thus assume that at least a unit amount of energy $\Delta$ must be replenished at each charging. That is, the amount of energy charged to a sensor $v_i \in V_s$ at each time is a value in $\{\Delta, 2\Delta, \ldots, k_i\Delta, B_i - RE_i\}$, where $k_i = \lfloor \frac{B_i - RE_i}{\Delta} \rfloor$ is an integer. Assume that the value of $\Delta$ is large enough so that the value of $\max_{v_i \in V_S}\{\lfloor \frac{B_i}{\Delta} \rfloor\}$ is bounded by a constant $k_{max}$, e.g., $k_{max} = 5$.

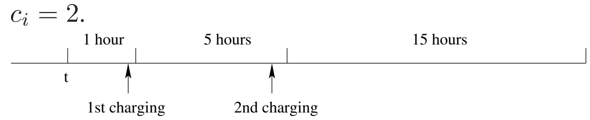
Recall that each sensor $v_i$ may be charged multiple times during a mobile charger tour and the accumulated amount of energy received by sensor $v_i$ is $B_i - RE_i$. We assume that sensor $v_i$ is charged by the mobile charger $c_i$ times and an amount $e_i^j$ of energy is charged at time $t_i^j$, where $1 \le j \le c_i$ and $c_i$ is a positive constant with $c_i \le \lceil \frac{B_i - RE_i}{\Delta} \rceil$ as $\Delta$ is the energy charging unit. Then, $\sum_{j=1}^{c_i} e_i^j = B_i - RE_i$. Denote by $RE_i^j$ the residual energy of sensor $v_i$ after the $j$th charging with $0 \le j \le c_i$. Note that $RE_i^0$ is the amount of residual energy of sensor $v_i$ before any charging, i.e., $RE_i^0 = RE_i$. Then, sensor $v_i$ will not deplete its energy before the $(j+1)$th charging if $t_i^{j+1} \le t_i^j + \frac{RE_i^j}{\rho_i}$. Otherwise, it will run out of its energy from time $t_i^j + \frac{RE_i^j}{\rho_i}$ to time $t_i^{j+1}$.

A *charging tour* $C$ of the mobile charger for sensors in $V$ is defined as an order of pairs $(r, 0) \to (v'_1, e_1) \to (v'_2, e_2) \to \ldots \to (v'_{n'}, e_{n'}) \to (r, 0)$ with starting from and ending at depot $r$, where $v'_j$ is a sensor in $V$, $e_j$ is the amount of energy charged to sensor $v'_j$. A sensor can be charged multiple times in tour $C$, and $n' \ge n = |V|$. Denote by $w(C)$ the total length of tour $C$, i.e., $w(C) = \sum_{i=0}^{n'} d_{i,i+1}$, where $d_{i,i+1}$ is the Euclidean distance between nodes $v'_i$ and $v'_{i+1}$, and $v'_0 = v'_{n'+1} = r$.

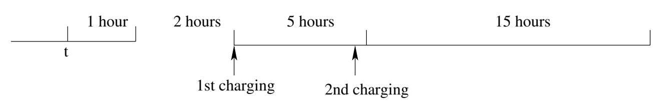
We assume that the total traveling time of the mobile charger per charging tour is much shorter than its time spent on charging sensors, but not negligible. For example, it may take about one minute for the mobile charger traveling to the location of a sensor from its last charging sensor location, assuming the distance of the two sensors is 300 meters away and the traveling speed of the charger is $5\ m/s$ [7], i.e., $60\ s = \frac{300\ m}{5\ m/s}$. It then takes the charger 10 minutes to charge an amount $\Delta$ of energy to the sensor. Therefore, we assume that the traveling time of the charger from its current charging sensor location to its next to-be-charged sensor location can be approximated by a constant $t_{travel}$, e.g., $t_{travel} = 1$ minute. The value of $t_{travel}$ can be predicted through historic charging. Therefore, we divide time into equal time slots with each lasting $\tau$ units, i.e., $\tau = \frac{\Delta}{\mu} + t_{travel}$, where $\frac{\Delta}{\mu}$ is the time spent by the charger for charging an amount $\Delta$ of energy to a sensor and $\mu$ is the charging rate. We index the time slots by $1, 2, \cdots$.

### C. Notions and notations

Recall that each sensor $v_i$ will be charged by the mobile charger $c_i$ times in its current charging tour and an amount $e_i^j$ of energy will be charged to $v_i$ at time $t_i^j$, where $1 \le j \le c_i$ and $\sum_{j=1}^{c_i} e_i^j = B_i - RE_i$. We say that sensor $v_i$ is charged *in time* by the mobile charger if and only if it can operate from time $(t + l_i)$ to $(t + l_i + \frac{B_i - RE_i}{\rho_i})$ $(= t + \frac{B_i}{\rho_i})$ without any energy depletions, where $l_i = \frac{RE_i}{\rho_i}$ is the residual lifetime of sensor $v_i$ at time $t$. In other words, sensor $v_i$ will not run out of energy before each of its $c_i$ chargings, i.e., $t_i^j \le t + l_i + \frac{\sum_{j'=1}^{j-1} e_i^{j'}}{\rho_i}$ for each $j$ with $1 \le j \le c_i$, where $t_i^j$ is the time at which the charger performs the $j$th charging to sensor $v_i$ and $\sum_{j'=1}^{j-1} e_i^{j'}$ is the accumulated amount of energy charged to sensor $v_i$ in the first $(j-1)$th chargings. Fig. 1 (a) illustrates that sensor $v_i$ is charged by the mobile charger in time, where $l_i = 1$ hour and $c_i = 2$.




(a) sensor $v_i$ is charged in time




(b) sensor $v_i$ has depleted its energy 2 hours already before the mobile charger charges it for the first time

Fig. 1. the mobile charger charges sensor $v_i$ with $c_i = 2$ chargings and the residual lifetime $l_i$ of sensor $v_i$ at time $t$ is 1 hour.

We note that the mobile charger may not be able to charge every sensor $v_i$ in time and the sensor may deplete its energy several times before its last (i.e., the $c_i$th) charging in the current charging tour, especially when there are a large number of life-critical sensors to be charged per tour. Fig. 1 (b) illustrates that sensor $v_i$ has depleted its energy completely 2 hours before the mobile charger performs charging to it. After the last charging, sensors $v_i$ will not run out of energy until time $t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}$, where $t_i^{c_i}$ is the time that the charger performs the last charging and $RE_i^{c_i}$ is the residual energy of sensor $v_i$ after its last charging. Denote by $l_{live}^i$ and $l_{dead}^i$ the total live duration and dead duration of sensor $v_i$ from time $t + l_i$ to time $t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}$, where $t + l_i$ is the time point that sensor $v_i$ will run out of energy if the mobile charger does not charge the sensor and $t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}$ is the time point that the sensor will deplete its energy after the mobile charger has performed the last charging to the sensor. We thus define the *normalized lifetime* $\eta_i$ of each sensor $v_i$ as

$$\eta_i = \frac{l_{live}^i}{l_{live}^i + l_{dead}^i}, \tag{1}$$

where $l_{live}^i = \frac{B_i - RE_i}{\rho_i}$ as an amount $B_i - RE_i$ of energy will be charged to sensor $v_i$. For example, in Fig. 1 (b), $l_{live}^i =$

$5+15=20$ hours and $l^i_{dead}=2$ hours. Then, $\eta_i=\frac{20}{20+2}=\frac{10}{11}$. Note that if sensor $v_i$ does not deplete its energy before any of the $c_i$ chargings, its normalized lifetime is $\eta_i=\frac{l^i_{live}}{l^i_{live}+l^i_{dead}}=\frac{l^i_{live}}{l^i_{live}+0}=1$ since $l^i_{dead}=0$ in this case, which is shown in Fig. 1 (a) with $l^i_{live}=20$ hours. The sum of normalized lifetimes $\eta_{sum}$ of sensors in $V$ then is

$$\eta_{sum}=\sum_{v_i\in V}\eta_i. \tag{2}$$

Recall that the normalized lifetime $\eta_i$ of each sensor $v_i$ implies the proportion of time that the sensor lives, which also can be interpreted as its live probability at any time point, by a charging tour if the charger replenishes sensor energy along the tour. The sum of normalized lifetimes $\eta_{sum}$ thus represents the expected number of live sensors maintained in the network by the charging tour.

### D. Problem definitions

It is desirable that every sensor should be charged before its energy depletion, this goal however may not be met, since the energy consumption rates of sensors may vary over time and cannot be precisely predicted. Therefore, sometimes there may be a large number of to-be-charged sensors in the network and the mobile charger is not able to charge each of them before its energy expiration. As continuing operations of sensors is a fundamental requirement for most WSNs, the *sensor lifetime maximization problem* is defined as follows. Given a set $V$ of to-be-charged sensors in network $G_s$ at some time point $t$, for each sensor $v_i\in V$, denote by $RE_i$ its residual energy, $\rho_i$ its energy consumption rate, and $B_i-RE_i$ its energy charging demand. Recall that the mobile charger has a charging rate $\mu$. The problem is to find a charging tour $C$ for the mobile charger to charge the sensors in $V$ so that the sum of the normalized lifetimes $\eta_{sum}$ of sensors in $V$ is maximized, subject to that the total amount of energy charged to each sensor $v_i\in V$ is equal to its energy demand $B_i-RE_i$. Denote by $\eta^*_{sum}$ the maximum sum of normalized lifetimes of all sensors in the WSN.

Assume that the maximum sum of normalized lifetimes $\eta^*_{sum}$ is given (the calculation of $\eta^*_{sum}$ will be shown later), it is desirable to minimize the traveling distance of the mobile charger due to its mechanical movement consuming lots of energy [15]. Given a set $V$ of to-be-charged sensors, let $C=<(r,0)\rightarrow(v'_1,e_1)\rightarrow(v'_2,e_2)\rightarrow\ldots\rightarrow(v'_{n'},e_{n'})\rightarrow(r,0)>$ be a charging tour of the mobile charger with starting from and ending at depot $r$, where $v'_j$ is a sensor in $V$, $e_j$ is the amount of energy charged to sensor $v'_j$, and each sensor $v_i$ in $V$ may be charged multiple times in the tour. We then define *the service cost minimization problem with the maximum sensor lifetime* as to find a charging tour $C$ for the mobile charger so that its traveling distance, $w(C)$, is minimized, subject to that the maximum sum of the normalized lifetimes $\eta^*_{sum}$ of all sensor can be achieved, i.e.,

$$mininize\quad w(C), \tag{3}$$

subject to

$$\sum_{v'_j\in C \& v'_j=v_i} e_j \quad\leq\quad B_i-RE_i,\quad \forall v_i\in V \tag{4}$$

$$\eta_{sum}\quad=\quad\eta^*_{sum}, \tag{5}$$

where constraint (4) ensures that the total amount of energy charged to each sensor $v_i$ in tour $C$ is no greater than its energy demand $B_i-RE_i$ and constraint (5) ensures that the sum of normalized lifetimes of all sensors is maximized. The problem is NP-hard, since the well-known NP-hard traveling salesman problem (TSP) is a special case of it.

## III. Algorithm for the Sensor Lifetime Maximization Problem

In this section, we devise an efficient algorithm for the sensor lifetime maximization problem. Given a set $V$ of to-be-charged sensors at some time point $t$ with the residual energy $RE_i$, energy consumption rate $\rho_i$, and the amount of energy demand $B_i-RE_i$ of each sensor $v_i$, the basic idea behind the algorithm is that the mobile charger can charge a sensor with an amount $\Delta$ of energy at every time slot for a monitoring period. We then can reduce the problem to a matching problem between sensors and time slots.

### A. Algorithm

Given a set $V$ of to-be-charged sensors, we create $k_i$ virtual sensors $v_{i,1},v_{i,2},\ldots,v_{i,k_i}$ for each sensor $v_i\in V$, where $k_i=\lceil\frac{B_i-RE_i}{\Delta}\rceil$, $B_i$ and $RE_i$ are the energy capacity and residual energy of sensor $v_i$, respectively, and $\Delta$ is an energy charging unit. We can see that only one time slot is needed to charge every virtual sensor. Let $V'=\{v_{i,j}\mid v_i\in V, 1\leq j\leq k_i\}$ be the set of virtual sensors and $k_{max}=\max_{v_i\in V}\{k_i\}$. Also, let $V'_j=\{v_{i,j}\mid v_{i,j}\in V'\}$ be the set of the $j$th virtual sensors of all sensors in $V'$ and $n'_j=|V'_j|$ withe $1\leq j\leq k_{max}$. We can see that sets $V'_1,V'_2,\ldots,V'_{k_{max}}$ form a partition of set $V'$, i.e., $V'_j\cap V'_{j'}=\emptyset$ if $j\neq j'$ with $1\leq j,j'\leq k_{max}$, and $V'=\cup_{j=1}^{k_{max}}V'_j$.

We iteratively find time slots at which the mobile charger charges virtual sensors in $V'$. That is, we find the time slots for charging virtual sensors in $V'_j$ in the $j$th iteration with $1\leq j\leq k_{max}$. Specifically, denote by $l_{i,j}$ and $l^{i,j}_{dead}$ the energy expiration time slot and dead duration of each sensor $v_i\in V$ before the $j$th charging (i.e., the $j$th iteration), respectively. Initially, $l_{i,1}=l_i$ and $l^{i,1}_{dead}=0$, where $1\leq i\leq n$. Let $G'_0$ be an empty graph, i.e., $G'_0=\emptyset$, and $S'=\{s_1,s_2,\ldots,s_{n'}\}$ be a set of $n'(=|V'|)$ time slots. In the $j$th iteration ($1\leq j\leq k_{max}$), we first construct a bipartite graph $G'_j=(\cup_{j'=1}^{j}V'_{j'},S',E'_j;w'_j)$ from graph $G'_{j-1}=(\cup_{j'=1}^{j-1}V'_{j'},S',E'_{j-1};w'_{j-1})$ and the virtual sensor set $V'_j$ as follows. First, let $E'_j=E'_{j-1}$, the weight $w'_j(v_p,s_q)$ of each edge $(v_p,s_q)\in E'_{j-1}$ in graph $G'_j$ is set to zero, rather than $w'_{j-1}(v_p,s_q)$ in graph $G'_{j-1}$. We then add an edge $(v_{i,j},s_q)$ to $E'_j$ for each virtual sensor $v_{i,j}\in V'_j$ and each time slot $s_q\in S'$. The weight $w'_j(v_{i,j},s_q)$ of edge $(v_{i,j},s_q)$ is equal to the normalized sensor lifetime of sensor $v_i$ if the charger performs the $j$th charging to it at time slot $s_q$, i.e., $w'_j(v_{i,j},s_q)=\frac{l^i_{live}}{l^i_{live}+l^{i,j}_{dead}}$ if $q\leq l_{i,j}+1$ as the sensor will not run out of its energy until time slot $l_{i,j}+1$; otherwise, $w'_j(v_{i,j},s_q)=\frac{l^i_{live}}{l^i_{live}+l^{i,j}_{dead}+q-l_{i,j}-1}$, since the dead duration of sensor $v_i$ will be prolonged from $l^{i,j}_{dead}$ to $l^{i,j}_{dead}+q-l_{i,j}-1$ if the $j$th charging to the sensor is performed at time slot $s_q$. We then find a maximum weighted matching $M_j$ in graph $G'_j$. Consider each virtual sensor $v_{i,j}\in V'_j$, assume that it is matched to time slot $s_q$ in matching $M_j$. If $q\leq l_{i,j}+1$, we remove the adjacent edges $(v_{i,j},s_{q'})$ of $v_{i,j}$ from graph $G'_j$ with $q'>l_{i,j}+1$, since sensor $v_i$ is charged in time at the $j$th charging. Otherwise, we remove the adjacent edges $(v_{i,j}, s_{q'})$ of sensor $v_{i,j}$ with $q' \neq q$. Finally, we obtain the energy expiration time $l_{i,j+1}$ of sensor $v_i$ before the $(j+1)$th charging (i.e., iteration) by charging sensor $v_i$ at time slot $s_q$ as virtual sensor $v_{i,j}$ is matched to time slot $s_q$ in matching $M_j$, and the dead duration of sensor $v_i$ before the $(j+1)$th charging is $l_{dead}^{i,j+1} = l_{dead}^{i,j} + \max\{q - l_{i,j} - 1,\ 0\}$. After the $k_{max}$th iteration, we obtain the time slot assigned to each virtual sensor in $V'$ by matching $M_{k_{max}}$.

The detailed algorithm is given in Algorithm 1.

**Algorithm 1** finding a charging tour with the maximum sensor lifetime

**Input:** A set $V$ of to-be-charged sensors with the residual energy $RE_i$, energy consumption rate $\rho_i$, and energy demand $B_i - RE_i$ of each sensor $v_i$.

**Output:** a charging tour $C$ of the mobile charger so that the sum of normalized sensor lifetimes is maximized

Create $k_i$ virtual sensors $v_{i,1}, v_{i,2}, \ldots, v_{i,k_i}$ for each sensor $v_i$ in $V$, where $k_i = \lceil \frac{B_i - Re_i}{\Delta} \rceil$. Let $V'_j = \{v_{1,j}, v_{2,j}, \ldots, v_{n,j}\}$, where $1 \leq j \leq k_{max}$;
Let $l_{i,1} = l_i = \lfloor \frac{RE_i}{\tau \rho_i} \rfloor$, $l_{dead}^{i,1} = 0$, graph $G'_0 = \emptyset$, and $S' = \{s_1, s_2, \ldots, s_{n'}\}$ with $n' = \sum_{i=1}^{n} k_i$;
**for** $j \leftarrow 1$ to $k_{max}$ **do**
  Construct bipartite graph $G'_j = (\cup_{j'=1}^{j} V'_{j'}, S', E'_j; w'_j)$ from $G'_{j-1} = (\cup_{j'=1}^{j-1} V'_{j'}, S', E'_{j-1}; w'_{j-1})$ and set $V'_j$;
  Find a maximum weighted matching $M_j$ in $G'_j$;
  For each $v_{i,j} \in V'_j$, assume that it is matched to time slot $s_q$ in $M_j$, remove its adjacent edges $(v_{i,j}, s_{q'})$ from graph $G'_j$ with $q' > l_{i,j} + 1$ if $q \leq l_{i,j} + 1$; otherwise, remove its adjacent edges $(v_{i,j}, s_{q'})$ with $q' \neq q$;
  For each $v_{i,j} \in V'_j$, obtain the energy expiration time $l_{i,j+1}$ of sensor $v_i$ before the $(j+1)$th charging by charging sensor $v_i$ at time slot $s_q$. The dead duration of sensor $v_i$ before the $(j+1)$th charging is $l_{dead}^{i,j+1} = l_{dead}^{i,j} + \max\{q - l_{i,j} - 1,\ 0\}$;
**end for**
Obtain the time slot assigned to each virtual sensor from matching $M_{k_{max}}$ and then find a charging tour $C$.

### B. Algorithm analysis

The analysis of `Algorithm 1` can be distinguished into two cases: there are only a very limited number of sensors to be charged; and there are a large number of sensors to be charged. Specifically, in case one, we assume that the lifetime of any sensor for consuming an amount $\Delta$ of energy is no less than the total time of charging every sensor in $V$ with an amount $\Delta$ of energy, i.e., $\frac{\Delta}{\rho_{max}} \geq n\tau$ (or $n \leq \frac{\Delta}{\tau \rho_{max}}$), where $\rho_{max} = \max_{v_i \in V}\{\rho_i\}$ is the maximum energy consumption rate of sensors in $V$, $\tau = \frac{\Delta}{\mu} + t_{travel}$ is the time for charging an amount $\Delta$ of energy to a sensor, $\mu$ is the charging rate of the mobile charger, and $t_{travel}$ is the traveling time from a charging sensor to the next charging sensor, and $t_{travel}$ is considered as a small constant.

*Theorem 1:* Given a set $V$ of to-be-charged sensors with the residual energy $RE_i$, energy consumption rate $\rho_i$, and energy demand $B_i - RE_i$ of each sensor $v_i \in V$, there is a heuristic algorithm, `Algorithm 1`, for the sensor lifetime maximization problem with time complexity $O(n^3)$, where $n = |V|$. Furthermore, the algorithm finds an optimal solution to the problem for Case one with $n \leq \frac{\Delta}{\tau \rho_{max}}$.

*Proof:* We omit the detailed analyses of the time complexity and the optimality of the solution delivered by Algorithm 1 when $n \leq \frac{\Delta}{\tau \rho_{max}}$ due to space limitation. ■

## IV. Algorithm for the service cost minimization problem with the maximum sensor lifetime

We have found a charging tour for the mobile charger so that the sum of the normalized sensor lifetimes of all sensors in the WSN is maximized. However, the service cost of the mobile charger per charging tour may not be cheap. In this section, we focus on minimizing the service cost of the mobile charger while ensuring that the maximum sum of normalized sensor lifetimes of sensors can be achieved, by proposing a novel heuristic algorithm. In the following, we first introduce the basic idea of the algorithm and then elaborate it in detail.

### A. Algorithm overview

Recall that we have created $k_i$ virtual sensors $v_{i,1}, v_{i,2}, \ldots, v_{i,k_i}$ for each sensor $v_i$ in $V$, and $V' = \{v_{i,j} \mid v_i \in V, 1 \leq j \leq k_i\}$, where $k_i = \lceil \frac{B_i - RE_i}{\Delta} \rceil$. Each virtual sensor $v_{i,j} \in V'$ has its energy expiration time $l_{i,j}$ in `Algorithm 1`. Also, in matching $M_{k_{max}}$, virtual sensor node $v_{i,j}$ is matched to a time slot node $s_q$. We term that a virtual sensor $v_{i,j}$ is *unexpired* if it is charged in time by matching $M_{k_{max}}$, i.e., $q \leq l_{i,j} + 1$. Otherwise ($q > l_{i,j} + 1$), it is *expired*. For the depot $r$ of the mobile charger, we create two virtual nodes $r_s$ and $r_f$ and the location of each of the two nodes is the same as that of depot $r$. The basic idea behind the heuristic algorithm is to find a $r_f$-rooted tree $T$ spanning nodes in $V' \cup \{r_s, r_f\}$ so that the weight of the tree is minimized, subject to that the number of virtual sensors in the subtree rooted at each unexpired virtual sensor $v_{i,j}$ is no more than its energy deadline $l_{i,j} + 1$, and the number at each expired virtual sensor $v_{i,j}$ is equal to $q$, assuming that $v_{i,j}$ is matched to the $q$th time slot in matching $M_{k_{max}}$. We then transform tree $T$ into a path $P$ starting from $r_s$ and ending at $r_f$ and the mobile charger charges sensors in $V$ along the path $P$.

### B. Algorithm

We now construct the tree $T$. We first partition the nodes in $V'$ into $n' = |V'|$ disjoint sets $V'_1, V'_2, \ldots, V'_{n'}$, where an expired virtual sensor in $V'$ is contained in set $V'_q$ if the sensor is matched to time slot $s_q$ in matching $M_{k_{max}}$, while an unexpired virtual sensor $v_{i,j} \in V'$ is contained in a set $V'_{j'}$ where $j'$ is the maximum integer no greater than $\min\{l_{i,j} + 1, n'\}$ so that there are no expired virtual sensors in each set $V'_{j''}$ with $j' < j'' \leq \min\{l_{i,j} + 1, n'\}$. In other words, $j'$ is the latest time slot that virtual sensor $v_{i,j}$ will not deplete its energy if the mobile charger can charge it prior to that time slot. Note that some of the $n'$ sets may contain none of virtual sensors. We can see that the number of nodes in the first $j$ sets is no more than $j$, i.e., $\sum_{j'=1}^{j} |V'_{j'}| \leq j$, for each $j$ with $1 \leq j \leq n'$. Having the $n'$ partitioned sets, we group them into $Y$ supersets $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_Y$, where $Y$ is the number of integers satisfying that $\sum_{j'=1}^{j} |V'_{j'}| = j$ with $1 \leq j \leq n'$. That is, assuming that the first $y-1$ superset $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_{y-1}$ contains the first $j_{y-1}$ sets $V'_1, V'_2, \ldots, V'_{j_{y-1}}$, superset $\mathcal{V}_y$ then contains sets $V'_{j_{y-1}+1}, V'_{j_{y-1}+2}, \ldots, V'_{j_y}$, where $\sum_{j'=1}^{j_y} |V'_{j'}| = j_y$ and $1 \leq y \leq Y$. We can see that the mobile charger must charge virtual sensors in superset $\mathcal{V}_{y-1}$ before charging any virtual sensor in superset $\mathcal{V}_y$ for each $y$ with $1 \leq y \leq Y$. Therefore, we can consider the charging sequence of the virtual sensors in $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_Y$ one by one. The detailed construction of tree $T$ is given as follows.

Let $V'_0 = \{r_s\}$ and $V'_{n'+1} = \{r_f\}$. We add the nodes in sets $V'_0, V'_1, V'_2, \ldots, V'_{n'}$ to tree $T$ one by one. Initially, $T$ contains only node $r_s$. Assume that the nodes in sets $V'_0, V'_1, V'_2, \ldots, V'_j$ have been added to $T$ and $V'_j$ is not an empty set. Consider the next non-empty set $V'_k$ with $k > j$. Assume that set $V'_k$ is contained in superset $\mathcal{V}_y$. We find a subtree $T_k$ that contains virtual sensors in $V'_k$ and other $k - \sum_{j'=1}^{k} |V'_{j'}|$ unexpired residual virtual sensors in superset $\mathcal{V}_y$ so that the weighted sum of edges in $T_k$ plus the minimum weight between $T_k$ and the nodes in $V'_j$ is minimized. To this end, for each unexpired residual virtual sensor $v_i$ in superset $\mathcal{V}'_y$, we obtain a subtree $T^i_k$ from a subtree containing only node $v_i$ to a subtree contains virtual sensors in $V'_k \cup \{v_i\}$ and other $k - \sum_{j'=1}^{j} |V'_{j'}| - |V'_k \cup \{v_i\}|$ unexpired virtual sensors in a greedy way. Subtree $T_k$ then is the tree with the minimum sum of tree weight plus the weight to nodes in $V'_j$, i.e., $T_k = \arg\min_{T^i_k}\{w(T^i_k) + w(e_{i,j})\}$, where $e_{i,j}$ is the minimum weighted edge between node $v_i$ and the nodes in $V'_j$. Finally, we attach subtree $T_k$ to the nearest node in $V'_j$ in tree $T$ and remove the nodes in $T_k$ from $V'_{k+1}, V'_{k+2}, \ldots, V'_{n'}$. After we have added nodes in $V'_0 \cup V'_1 \cup V'_2 \cup \ldots \cup V'_{n'}$ to tree $T$, we connect node $r_f$ to its nearest node in $V'_n$.

The rest is to transform tree $T$ to a path $P$ from node $r_s$ to node $r_f$ while visiting nodes in $V'$. We first find the path from node $r_s$ to node $r_f$ in tree $T$. We then obtain a graph $G''$ by replicating the edges in tree $T$ except the edges on the path and find a Eulerian path from node $r_s$ to node $r_f$ in graph $G''$. We finally find a path $P$ by shortcutting repeated nodes in the Eulerian path.

The detailed algorithm is given in Algorithm 2.

We here use an example taken from our experiments to illustrate the execution of Algorithm 2. Assume that there are three to-be-charged sensors $v_1, v_2$, and $v_3$ in the network at some time point (see Fig. 2 (a)), and their residual lifetimes are 0, 1, and 4 time slots, respectively. Two virtual sensors $v_{i,1}$ and $v_{i,2}$ are created for each sensor $v_i$ with$1 \leq i \leq 3$ (see Fig. 2 (b)). The energy expiration time and the matched time slot in matching $M_{k_{max}}$ found by Algorithm 1 are shown in Table I. The partitioned six virtual sets by Algorithm 2 are $V'_1 = \{v_{1,1}\}$, $V'_2 = \{v_{2,1}\}$, $V'_3 = \{\}$, $V'_4 = \{v_{3,1}\}$, $V'_5 = \{\}$, $V'_6 = \{v_{1,2}, v_{2,2}, v_{3,2}\}$, respectively. The six virtual sets are then grouped into three supersets $\mathcal{V}_1 = \{V'_1\}$, $\mathcal{V}_2 = \{V'_2\}$, and $\mathcal{V}_3 = \{V'_3, V'_4, V'_5, V'_6\}$, respectively. Initially, tree $T$ contains only node $r_s$. Virtual sensors in $V'_1, V'_2, \ldots, V'_6$ are added to $T$ one by one, and a subtree $T_j$ is found for each virtual set $V'_j$, $1 \leq j \leq 6$. Since virtual set $V'_1$ contains only one node $v_{1,1}$, a subtree $T_1$ containing only node $v_{1,1}$ is attached to tree $T$ by connecting node $v_{1,1}$ to node $r_s$ that is the nearest node in $V'_0 = \{r_s\}$ (see Fig. 2 (c)). Similarly, a subtree $T_2$ containing only node $v_{2,1} \in V'_2$ is added to tree $T$ by connecting $v_{2,1}$ to node $v_{1,1}$ that is the nearest node in $V'_1 = \{v_{1,1}\}$ (see Fig. 2 (d)). For virtual set $V'_4 = \{v_{3,1}\}$ (set $V'_4$ is contained in superset $\mathcal{V}_3$), a subtree $T_4$ is found so that the subtree contains the node $v_{3,1}$ in $V'_4$ and other $4 - \sum_{j=1}^{4} |V'_j| = 4 - 3 = 1$ node in set $\cup_{V'_j \in \mathcal{V}_3} V'_j \setminus V'_4 = \{v_{3,1}, v_{1,2}, v_{2,2}, v_{3,2}\} \setminus \{v_{3,1}\} = \{v_{1,2}, v_{2,2}, v_{3,2}\}$, and the sum of the weight of tree $T_4$ plus the weight of the shortest edge between $T_4$ and the node in $V'_2$ is

**Algorithm 2** finding a shortest charging tour with the maximum sensor lifetime

**Input:** Virtual sensor set $V'$, their energy expiration times $l_{i,j}$s, matching $M_{k_{max}}$, and depot $r$.
**Output:** a charging tour $P$ so that the length of the tour is minimized, while the sum of normalized sensor lifetimes is the same as that from matching $M_{k_{max}}$.

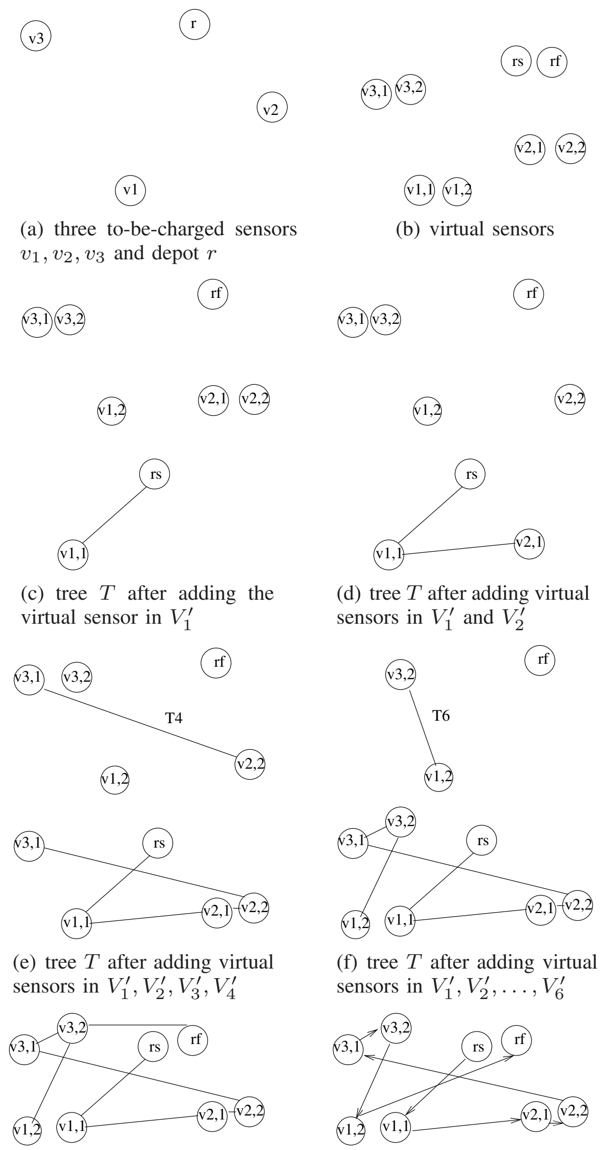
Partition virtual sensors in $V'$ into $n'$ sets $V'_1, V'_2, \ldots, V'_{n'}$ by their energy expiration times and matching $M_{k_{max}}$;
Group the $n'$ sets into $Y$ supersets $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_Y$;
Let set $V_0 = \{r_s\}$ and tree $T$ contain only node $r_s$;
**for** $k \leftarrow 1$ to $n'$ **do**
  **if** $V'_k$ contains virtual sensors **then**
    Let $n_k = k - \sum_{j'=1}^{k-1} |V'_{j'}|$; // # of nodes in tree $T_k$;
    Assume that $j$ is the maximum index so that $V'_j$ contains virtual sensors with $0 \leq j < k$;
    **if** $|V'_k| = n_k$ **then**
      Tree $T_k$ is an MST of a complete graph $G'_k = (V'_k, E'_k; w' : E'_k \mapsto \mathcal{R}^+)$, where $w'(u, v)$ is the Euclidean distance between any two virtual sensors $u$ and $v$ in $V'_k$;
    **else**
      Assume that set $V'_k$ is contained in superset $\mathcal{V}_y$;
      **for** each unexpired residual nodes $v_i \in \mathcal{V}_y$ **do**
        Obtain a minimum weighted tree $T^i_k$ covering nodes in set $V'_k \cup \{v_i\}$ and other $n_k - |V'_k \cup \{v_i\}|$ unexpired virtual sensors in superset $\mathcal{V}_y$ in a greedy way;
      **end for**
      Let $T_k = \arg\min_{T^i_k}\{w(T^i_k) + w(e_{i,j})\}$, where $e_{i,j}$ is the minimum weighted edge between node $v_i$ and nodes in $V'_j$;
    **end if**
    Expand tree $T$ by connecting subtree $T_k$ to nodes $V'_j$ using their minimum weighted edge;
    Let $V'_p \leftarrow V'_p \setminus V(T_k)$ for $k < p \leq n'$
  **end if**
**end for**
Add node $r_f$ to tree $T$ by connecting it to nodes in $V'_{n'}$ using their minimum weighted edge;
Obtain a graph $G''$ by replicating edges in tree $T$ except the edges on the path from nodes $r_s$ to $r_f$ in tree $T$;
Find a Eulerian path from nodes $r_s$ to $r_f$ in $G''$;
Obtain a charging tour $P$ by removing repeated nodes in the Eulerian path with shortcutting.

minimized, where tree $T_4$ contains virtual sensors $v_{3,1}$ and $v_{2,2}$ (see Fig. 2 (e)). After subtree $T_4$ has been attached to tree $T$, there are only two virtual sensors $v_{1,2}, v_{3,2}$ left in $V'_6$. Subtree $T_6$ then contains only the two nodes and it is attached to tree $T$ by connecting $v_{3,2}$ to $v_{3,1}$ (see Fig. 2 (f)). Finally, node $r_f$ is added to tree $T$ by connecting it to node $v_{3,2}$ that is its nearest node in set $V'_6$ (see Fig. 2 (g)). A charging tour $P$ is derived from tree $T$ (see Fig. 2 (h)), from which it can be seen that only sensor $v_1$ will be charged twice by the charger in the tour while both sensors $v_2$ and $v_3$ are charged only once, as two consecutive chargings for two virtual sensors derived from the same real sensor can be merged into one charging.

*Theorem 2:* Given a set $V$ of to-be-charged sensors with each sensor $v_i \in V$ having its residual energy $RE_i$, energy consumption rate $\rho_i$, and energy demand $B_i - RE_i$, there is a heuristic algorithm for the service cost minimization problem

TABLE I. THE ENERGY EXPIRATION TIME AND MATCHED TIME SLOT FOR EACH VIRTUAL SENSOR

| virtual sensor | $v_{1,1}$ | $v_{1,2}$ | $v_{2,1}$ | $v_{2,2}$ | $v_{3,1}$ | $v_{3,2}$ |
|---|---|---|---|---|---|---|
| expiration time | 0 | 862 | 1 | 173 | 4 | 78 |
| matched time slot | 1 | 4 | 2 | 5 | 3 | 6 |



(a) three to-be-charged sensors $v_1, v_2, v_3$ and depot $r$
(b) virtual sensors
(c) tree $T$ after adding the virtual sensor in $V_1'$
(d) tree $T$ after adding virtual sensors in $V_1'$ and $V_2'$
(e) tree $T$ after adding virtual sensors in $V_1', V_2', V_3', V_4'$
(f) tree $T$ after adding virtual sensors in $V_1', V_2', \ldots, V_6'$
(g) the finally found tree $T$
(h) the derived tour $P$ from tree $T$

Fig. 2. An example of Algorithm 2.

with the maximum sensor lifetime in time $O(|V|^4)$.

## V. PERFORMANCE EVALUATION

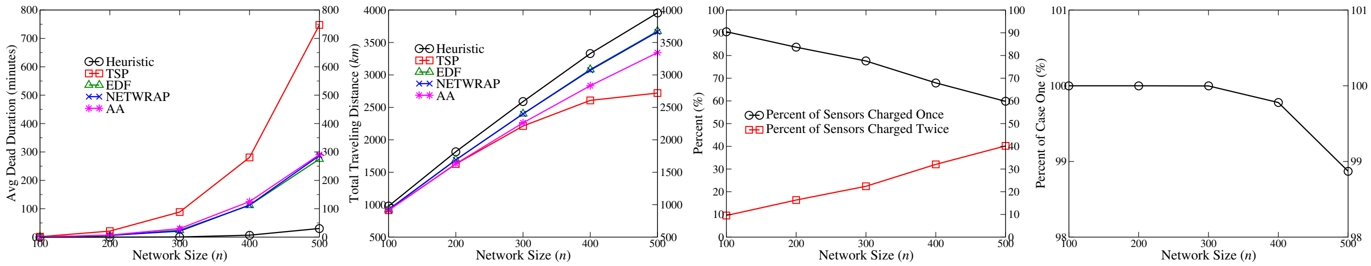
### A. Simulation environment

We consider a WSN consisting of from 100 to 500 sensors randomly deployed within a $1,000m \times 1,000m$ square area. Both the base station and the depot $r$ are co-located at the center of the square. The battery capacity of each sensor $v_i \in V_s$ is $B_i = B = 10.8\ kJ$ [11]. The data sensing rate $b_i$ of sensor $v_i$ is randomly chosen from an interval $[b_{min}, b_{max}]$, where $b_{min} = 1\ kbps$ and $b_{max} = 10\ kbps$ [11]. We adopt the real sensor energy consumption model in [5]. The mobile charger travels at a constant speed of $\nu = 5\ m/s$. The charging rate of the mobile charger is $\mu = 5\ Watts$ and the energy charging unit $\Delta$ for charging any sensor is from $\frac{B}{5}$ to $B$. Each to-be-charged sensor sends a charging request to the base station when its residual lifetime is below a critical lifetime $l_c = 2\ hours$. The given monitoring period $T$ is one year. Assume that each sensor $v_i$ will run out of its energy $d_i \geq 0$ times during the period $T$, and it stops working during the time interval $[t^s_{i,j}, t^f_{i,j}]$ due to its $j$th energy depletion, where $1 \leq j \leq d_i$ and $0 < t^s_{i,1} < t^f_{i,1} < t^s_{i,2} < t^f_{i,2} < \cdots < t^s_{i,d_i} < t^f_{i,d_i} \leq T$. Then, there is some residual energy in it in time intervals $[0, t^s_{i,1}], [t^f_{i,1}, t^s_{i,2}], \ldots, [t^f_{i,d_i-1}, t^s_{i,d_i}]$, and $[t^f_{i,d_i}, T]$. The dead duration of sensor $v_i$ then is calculated as $\sum_{j=1}^{d_i}(t^f_{i,j} - t^s_{i,j})$.

To evaluate the performance of the proposed algorithm `Heuristic`, we also implement algorithms `EDF`, `TSP`, `NETWRAP` in [12], and `AA` in [13]. In algorithm `EDF` (Earliest Deadline First), we sort to-be-charged sensors by their energy expiration deadlines and the mobile charger visits the sorted sensors one by one. In algorithm `TSP`, we calculate an approximately shortest closed tour visiting to-be-charged sensors without considering their energy expirations [1]. In algorithm `NETWRAP` [12], the mobile charger selects the next to-be-charged sensor that has the minimum weighted sum of the traveling time of the charger to the sensor and the residual lifetime of the sensor. Finally, in the state-of-the-art algorithm `AA` [13], a mobile charger charges a proportion of to-be-charged sensors before their energy expirations, so as to maximize the total amount of energy charged to sensors minus the total traveling energy cost of the charger. Each value in figures is the average of the results by applying each mentioned algorithm to 100 different network topologies with the same network size.

### B. Algorithm Performance

We first evaluate the performance of algorithms `Heuristic`, `TSP`, `EDF`, `NETWRAP`, and `AA` by varying the network size $n$ from 100 to 500, while keeping the energy charging unit $\Delta$ at $\frac{B}{2}$. Fig. 3 (a) shows the average energy dead duration per sensor delivered by these algorithms during the entire monitoring period $T$, from which it can be seen that the average dead duration per sensor by the proposed algorithm `Heuristic` is much shorter than that by algorithms `TSP`, `EDF`, `NETWRAP`, and `AA`. For example, the average dead duration by algorithm `Heuristic` is only around 10% of that by algorithm `AA`, i.e., $10\% \approx \frac{30.5\ minutes}{290.7\ minutes}$. The rationale behind is that algorithm `Heuristic` can find a charging tour so that the sum of normalized lifetimes of all sensors is maximized while the rest of the mentioned algorithms ignore minimizing the energy dead durations. Fig. 3 (a) also demonstrates that the average dead duration delivered by algorithm `TSP` is the longest one among the mentioned algorithms, since algorithm `TSP` does not consider the energy expirations of to-be-charged sensors and schedules the mobile charger to charge the sensors along a shortest tour. Fig. 3 (b) plots the total traveling distance of the mobile charger delivered by the mentioned algorithms during the period of $T$. Algorithm `Heuristic` has the longest total traveling distance, which is about from 7% to 18% longer than that by algorithm `AA`. Such a minor increase on the traveling distance however is worthy as the average dead duration per sensor by the algorithm is only about 10% of that by algorithm `AA`, while the continuing operation of sensors usually is a fundamental



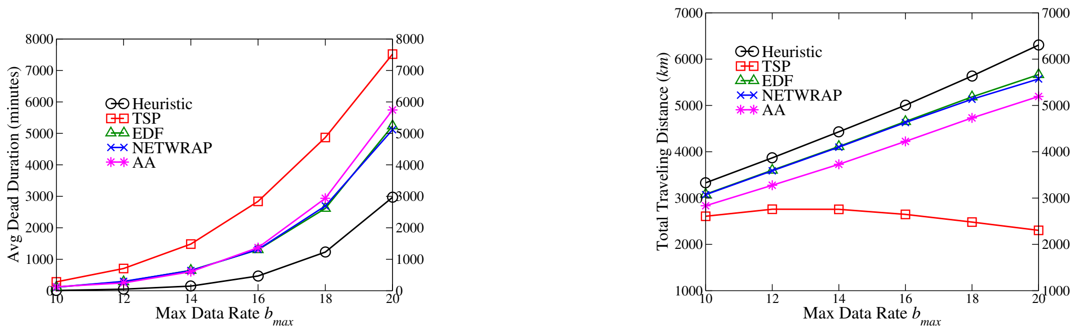

(a) Average dead duration per sensor during $T$

(b) Total traveling distance of the mobile charger during $T$

(c) The percentages of sensors charged once and twice, respectively

(d) Percent of case one

Fig. 3. Performance of algorithms `Heuristic`, `TSP`, `EDF`, `NETWRAP`, and `AA` by varying the network size $n$ from 100 to 500 while $\Delta = \frac{B}{2}$.




(a) Average dead duration per sensor during $T$

(b) Total traveling distance of the mobile charger during $T$

Fig. 4. Performance of algorithms `Heuristic`, `TSP`, `EDF`, `NETWRAP`, and `AA` by varying the maximum data rate $b_{max}$ from 10 $kbps$ to 20 $kbps$ while $b_{min} = 1$ $kbps$, $n = 400$, and $\Delta = \frac{B}{2}$.

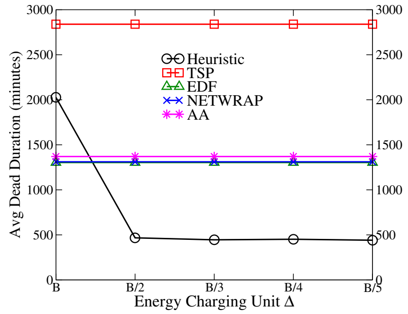
requirement in many WSN applications. Notice that although each to-be-charged sensor is allowed to be charged up to twice as $\Delta = \frac{B}{2}$, it is unnecessary that each sensor must be charged twice. Fig. 3 (c) demonstrates the percentages of sensors charged once and twice during a charging tour delivered by the proposed algorithm `Heuristic`, respectively, from which it can be seen that more than 60% of the sensors are charged only once. Finally, Fig. 3 (d) shows that, in as high as 98% of the chargings during period $T$, the number of to-be-charged sensors falls into Case one, for which algorithm `Heuristic` can deliver the maximum sum of the normalized lifetimes of sensors by Theorem 1.

We then study the performance of different algorithms, by varying the maximum data rate $b_{max}$ from 10 $kbps$ to 20 $kbps$ while setting $b_{min} = 1$ $kbps$, $n = 400$, and $\Delta = \frac{B}{2}$. Fig. 4 (a) implies that the average dead duration per sensor by each of the algorithms increases with the growth of $b_{max}$ from 10 $kbps$ to 20 $kbps$. As a result, there are more to-be-charged sensors in each charging tour, and each to-be-charged sensor thus is more likely to deplete its energy before it can be replenished. Fig. 4 (a) also indicates that the average dead duration per sensor by algorithm `Heuristic` is the shortest one while the one by algorithm `TSP` is the longest one. On the other hand, Fig. 4 (b) exhibits an interesting phenomenon. That is, the total traveling distance of the mobile charger delivered by any of algorithms `Heuristic`, `EDF`, `NETWRAP`, and `AA` becomes longer with the increase of $b_{max}$, while the one by algorithm `TSP` slightly decreases. The rationale is that there are more to-be-charged sensors in each charging tour when the maximum data rate $b_{max}$ increases, the number of charging tours during period $T$ however significantly decreases. Since the first four algorithms schedule the mobile charger by taking sensor energy expirations into consideration, the traveling distances by them in each tour will become significantly longer with the increase of $b_{max}$. In contrast, in algorithm `TSP`, although the increase on the number of to-be-charged sensors in each charging tour will increase the traveling distance of the mobile charger, such an increase is insignificant as algorithm `TSP` does not consider sensor energy expirations, and to-be-charged sensors usually are close to the base station.

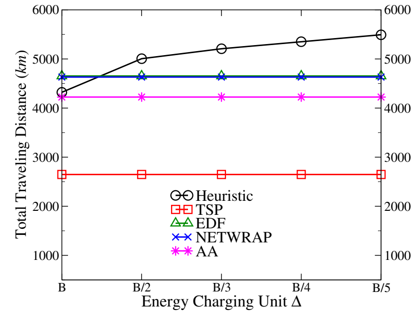
We finally investigate the impact of the energy charging unit $\Delta$ on algorithm performance, by decreasing $\Delta$ from $B$ to $\frac{B}{5}$. It can be seen that, $\Delta = B$ indicates that the full-charging model is adopted while $\Delta = \frac{B}{2}, \frac{B}{3}, \frac{B}{4}$, or $\frac{B}{5}$ means that the partial-charging model is adopted. Fig. 5 (a) implies that the average dead duration per sensor by algorithm `Heuristic` significantly decreases when the value of $\Delta$ decreases from $B$ to $\frac{B}{2}$. This demonstrates that the proposed partial-charging model can shorten sensor energy expiration durations. Fig. 5 (a) also indicates that the average dead duration by algorithm `Heuristic` slightly decreases with the decrease of $\Delta$ from $\frac{B}{2}$ to $\frac{B}{5}$. In contrast, Fig. 5 (a) shows that the performance of algorithms `TSP`, `EDF`, `NETWRAP`, and `AA` do not change with the decrease of $\Delta$ as they adopt the full-charging model. On the other hand, Fig. 5 (b) implies that the total traveling distance by algorithm `Heuristic` increases with the decrease of $\Delta$. In summary, when $\Delta = \frac{B}{2}$, the performance of algorithm `Heuristic` achieves the finest trade-off between minimizing the dead duration per sensor and minimizing the traveling distance of the mobile charger.

## VI. Related Work

Wireless energy replenishment as a promising mechanism for prolonging the lifetime of WSNs has been recently studied in literature [14], [8], [11], [12], [13], [2]. For example, Xu *et al.* [14] studied the problem of scheduling $k$ mobile chargers to charge a set of sensors so that the sensors can be fully charged as soon as possible, while Ren *et al.* [8] investigated




(a) Average dead duration per sensor during $T$




(b) Total traveling distance of the mobile charger during $T$

Fig. 5. Performance of algorithms `Heuristic`, `TSP`, `EDF`, `NETWRAP`, and `AA` by decreasing the energy charging unit $\Delta$ from $B$ to $\frac{B}{5}$ while $b_{min} = 1\ kbps$, $b_{max} = 16\ kbps$, and $n = 400$.

the problem of scheduling a mobile charger to charge as many sensors as possible within a given time period, by taking both the sensor charging time and the traveling time of the charger into consideration. Shi *et al.* [11] employed a wireless charger to periodically charge all sensors such that the network can perpetually operate. Wang *et al.* [12] proposed an algorithm in which a mobile charger selects the next to-be-charged sensor that has the minimum weighted sum of the traveling time of the mobile charger to the sensor and the residual lifetime of the sensor. Given a set of to-be-charged sensors with different residual lifetimes, they also provided an adaptive algorithm to schedule a mobile charger to charge a proportion of the sensors before their energy expirations, with the objective to maximize the total amount of energy charged to sensors minus the total traveling energy cost of the charger [13]. He *et al.* [2] investigated a mobile charging problem using a Nearest-Job-Next with preemption, and provided analytical results on the number of charging requests served and the charging latency of each sensor, assuming that the arrival times of sensor charging requests follow Poisson's distribution. Different from these mentioned studies that adopt a simple full-charging model, we are the first to adopt a novel partial-charging model so that more sensors can be charged before their energy depletion. Also, unlike the previous studies that ignore the energy expiration durations of sensors, we study the problem of scheduling a mobile charger to charge sensors so that the sum of normalized sensor lifetimes is maximized, while the traveling distance of the charger is minimized.

## VII. Conclusions

In this paper we studied the use of a mobile charger to wirelessly charge sensors in a rechargeable sensor network so that the sum of sensor survival times can be maximized while keeping the traveling distance of the mobile charger minimized. Unlike existing studies that assumed a mobile charger must charge a sensor to its full energy capacity before charging the next one, we are the first to propose a partial energy charging model for sensor charging to shorten sensor dead durations, under which we first formulated a novel optimization problem of scheduling the mobile charger to charge life-critical sensors such that the sum of the normalized lifetimes of sensors in the network is maximized, while keeping the traveling distance of the mobile charger minimized. We then proposed an efficient algorithm for the problem, and we finally evaluated the performance of the proposed algorithm through experimental simulation. The simulation results demonstrate that the proposed algorithm is very promising.

## Acknowledgment


The work by Wenzheng Xu was partially supported by 2016 Basic Research Talent Foundation of Sichuan University in China (Grant No. 2082204194050).


## References


[1] R. Diestel. *Graph Theory.* Springer-Verlag, 2000.

[2] L. He, Y. Gu, J. Pan, and T. Zhu. On-demand charging in wireless sensor networks: theories and applications. *Proc. of MASS*, IEEE, 2013.

[3] M. Hefeeda and M. Bagheri. Wireless sensor networks for early detection of forest fires. *Proc. of MASS*, IEEE, 2007.

[4] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljacic. Wireless power transfer via strongly coupled magnetic resonances. *Science*, vol. 317, pp. 83–86, 2007.

[5] J. Li and P. Mohapatra. Analytical modeling and mitigation techniques for the energy hole problem in sensor networks. *Pervasive Mobile Comput.*, vol. 3, pp. 233–254, 2007.

[6] W. Liang, W. Xu, X. Ren, X. Jia, and X. Lin. Maintaining large-scale rechargeable sensor networks perpetually via multiple mobile charging vehicles. *ACM Trans. Sensor Netw.*, to appear.

[7] W. Liang, W. Xu, X. Ren, X. Jia, and X. Lin. Maintaining sensor networks perpetually via wireless mobile recharging vehicles. *Proc. of LCN*, IEEE, 2014.

[8] X. Ren, W. Liang, and W. Xu. Maximizing charging throughput in rechargeable sensor networks. *Proc. of ICCCN*, IEEE, 2014.

[9] X. Ren, W. Liang, and W. Xu. Data collection maximization in renewable sensor networks via time-slot scheduling. *IEEE Trans. Comput.*, vol. 64, no.7, pp. 1870–1883, 2015.

[10] X. Ren, W. Liang, and W. Xu. Quality-aware target coverage in energy harvesting sensor networks. *IEEE Trans. Emerging Topics Comput.*, vol. 3, no. 1, pp. 8–21, 2015.

[11] Y. Shi, L. Xie, Y. T. Hou, and H. D. Sherali. On renewable sensor networks with wireless energy transfer. *Proc. of INFOCOM*, IEEE, 2011.

[12] C. Wang, J. Li, F. Ye, and Y. Yang. NETWRAP: an NDN based real-time wireless recharging framework for wireless sensor networks. *IEEE Trans. Mob. Comput.*, vol. 13, pp. 1283–1297, 2014.

[13] C. Wang, J. Li, F. Ye, and Y. Yang. Recharging schedules for wireless sensor networks with vehicle movement costs and capacity constraints. *Proc. of SECON*, IEEE, 2014.

[14] W. Xu, W. Liang, and X. Lin. Approximation algorithms for min-max cycle cover problems. *IEEE Trans. Comput.*, vol. 64, pp. 600–613, 2015.

[15] W. Xu, W. Liang, X. Lin, G. Mao, and X. Ren. Towards perpetual sensor networks vis deploying multiple mobile wireless chargers. *Proc. of ICPP*, 2014.

[16] W. Xu, W. Liang, X. Lin, and G. Mao. Efficient scheduling of multiple mobile chargers for wireless sensor networks. *IEEE Trans. Veh. Technol.*, to appear, DoI: 10.1109/TVT.2015.2496971.

[17] W. Xu, W. Liang, X. Ren, and X. Lin. On-demand energy replenishment for sensor networks via wireless energy transfer. *Proc. of PIMRC*, IEEE, 2014.

[18] M. Zhao, J. Li, and Y. Yang. Joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks. *Proc. of ITC*, IEEE, 2011.